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Speculative markets and the effectiveness of price limits

Frank Westerhoff

Department of Economics, University of Osnabrueck, Rolandstrasse 8, D-49069 Osnabrück, Germany

Abstract

The aim of this paper is to study the effectiveness of price limits in speculative markets. We construct a nonlinear stochastic asset pricing model in which traders rely on technical and fundamental analysis to determine their orders. The dynamics of the model mimic stylized facts such as the emergence of bubbles, excess volatility, fat tails for returns or volatility clustering quite well. Using this model as a laboratory, we find that price limits have the potential to reduce both volatility and deviations from fundamentals. The more traders lend themselves to trend-extrapolating behavior, the better price limits work.

JEL classification: G14; G15; G18

Keywords: Speculative markets; Price limits; Technical and fundamental trading rules

1. Introduction

Financial theory offers two competing kinds of volatility concepts. The efficient market hypothesis (Fama, 1970) assumes that prices always reflect the fundamental value. If they do not, rational agents start trading. Buying underpriced and selling overpriced assets pushes prices towards their fundamentals. Rational prices contribute to economic efficiency by directing resources toward their highest-value uses. If a market is hit by a fundamental shock, economic efficiency is best maintained by an immediate adjustment of prices to the new fundamental value (fundamental volatility concept).

The noise trader approach is less optimistic about the functioning of asset markets. According to Shleifer and Summers (1990), the behavior of some traders is affected by their beliefs. The influence of pseudo-signals like rumors and the use of popular models

E-mail address: fwesterho@oec.uni-osnabrueck.de (F. Westerhoff).

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like feedback rules lead to nonoptimal trading strategies. Since the financial resources of rational traders are limited, changes in investor sentiment are not fully countered and thus have an impact on asset prices (noise trader volatility concept). The noise trader approach has gained strong empirical support in recent years. As reported by the BIS (1999), transactions in foreign exchange markets largely reflect short-term speculative trading. Surprisingly, the traders rely on rather simple trading rules like technical or fundamental analysis to decide on their investments (Taylor and Allen, 1992).

If the activity of traders causes assets to be mispriced, it is interesting to ask whether there exist any means to regulate the markets. This paper focuses on price limits. Price limits interrupt the trading process when prices are about to exceed a pre-specified limit. Such trading halts may be beneficial if they protect the market from destabilizing trades. Although several papers deal with the usefulness of price limits, a final judgement has not yet been reached (Harris, 1998). One reason is that these studies encounter empirical drawbacks. For instance, without knowing the fundamental value of an asset, mispricing cannot be measured accurately.

To avoid such problems, we follow a novel track. Our aim is to develop a laboratory to study the impact of price limits on asset price dynamics. A chartist–fundamentalist framework (as proposed by Frankel and Froot (1986), Kirman (1991), Brock and Hommes (1997, 1998), Lux and Marchesi (2000) and Chiarella et al. (2002)) serves as our starting point. Based on empirical grounds, we construct a model in which the agents apply technical and fundamental analysis to determine their asset demand. Simulations show that our model is able to replicate stylized facts such as the emergence of bubbles, excess volatility, fat tails for returns and strong volatility clustering. Within this setting, price limits have the potential to reduce both volatility and distortion. Especially, if traders exhibit a bandwagon behavior, price limits are effective.

Our paper is organized as follows. In Section 2, we review some important stylized facts regarding speculative markets and survey the literature on price limits. In Section 3, we develop and calibrate our laboratory model on speculative market dynamics. Section 4 investigates the effectiveness of price limits and Section 5 draws some conclusions.

2. Empirical evidence

2.1. *Stylized facts of speculative markets*

This section outlines four stylized facts regarding speculative markets: (i) the emergence of bubbles, (ii) high volatility, (iii) fat tails for returns, and (iv) volatility clustering. To illustrate these phenomena, we proceed in two steps. First, we illustrate typical behavior by exploring the behavior of DEM/USD exchange rates with graphical means. Second, we quantify these properties and compare them for several markets. More extensive surveys on these universal features are provided by Guillaume et al. (1997) and Lux and Ausloos (2002).

The top panel of Fig. 1 displays daily DEM/USD exchange rates from 1974 to 1998. The mark–dollar exchange rate seems to hover around DM 1.80 in the final 10 years

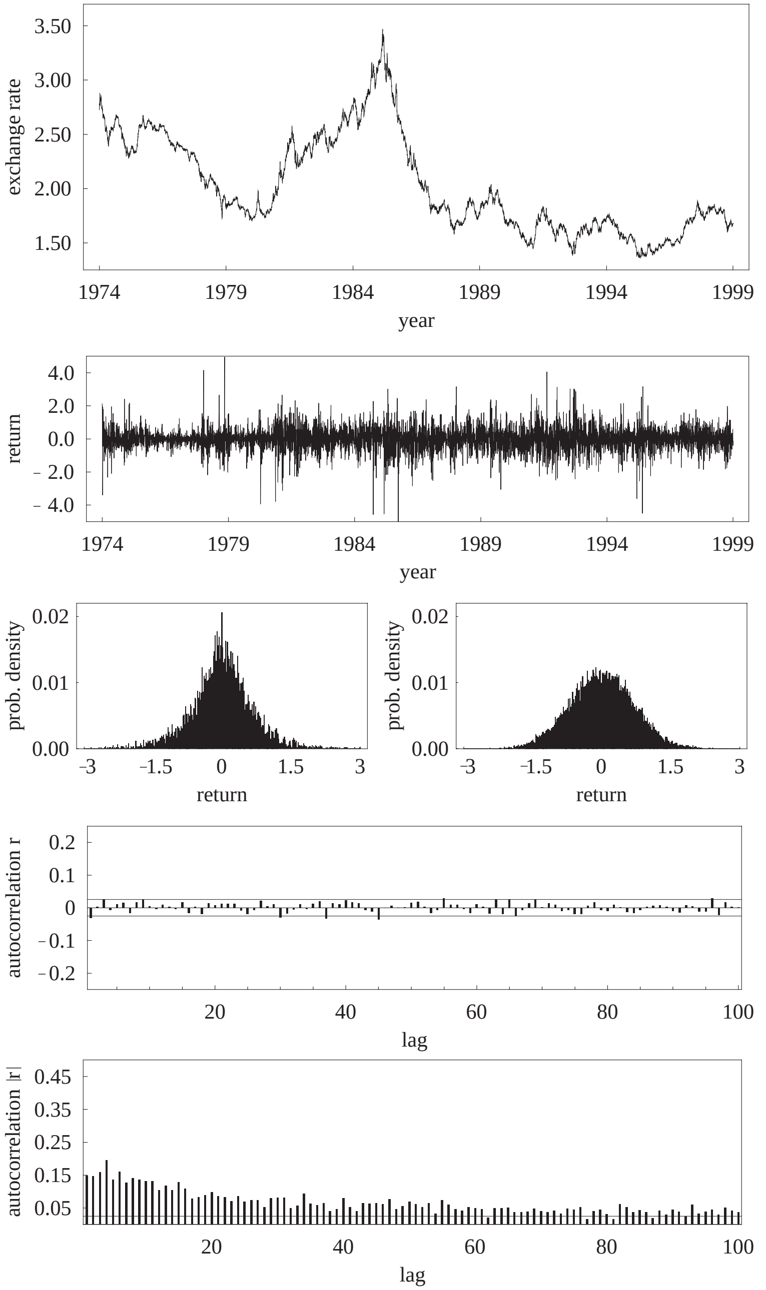

Fig. 1. DEM/USD exchange rate behavior. The first two panels show daily exchange rate and return dynamics from 1974 to 1998, the middle two panels the probability density function for DEM/USD returns (left) and normally distributed returns (right), and the last two panels show the autocorrelation functions for raw returns and absolute returns (with 95 percent confidence bands).

of the sample period. However, it is widely recognized that the dollar traced out a bubble path in the mid-1980s. From January 1980 to February 1985, the mark–dollar exchange rate rose from DM 1.70 to DM 3.46. But then the bubble bursts. At the end of 1987, the dollar again dropped to below DM 1.70. For Frankel and Froot (1986), at least the last 20 percent of the dollar appreciation cannot be attributed to fundamental forces.

In the second panel of Fig. 1, daily returns r (i.e. daily percentage price changes) are plotted. Some isolated exchange rate movements exceed the 5 percent level. Calculating average absolute returns as a proxy for volatility for this sample period yields a value of $V = 0.5$. Fluctuations of half a percent per day may be seen as excessive. This view is, for instance, supported by Guillaume et al. (1997), who report that distinct and relatively large price changes often appear unrelated to fundamental shocks. In their opinion, the price formation process is partially independent of the presence or absence of news.

The two central panels visualize the fat tail property. The left-hand side contains the probability density function for DEM/USD returns and the right-hand side shows the same for normally distributed returns (the same variance as DEM/USD returns). Compared to the normal distribution, one finds a higher concentration around the mean, thinner shoulders and more probability mass in the tails.

The final two panels display the autocorrelation function for raw returns and absolute returns. For almost all lags, the autocorrelation of raw returns is not significant. The autocorrelation of absolute returns, however, is clearly significant, indicating strong evidence of volatility clustering. It can also be seen in the second panel that periods of low volatility alternate with periods of high volatility.

Table 1 summarizes some of the facts just described for a broader range of markets. It comprises statistics for two stock indices, two currencies and two precious metals. The second and third columns indicate the sample period and sample length. The largest daily price movements range from 3.8 percent (DEM/JPY) to 33.2 percent (silver). Price changes of currencies seem to be somewhat lower than that of other markets. Average absolute returns scatter from $V = 0.44$ to 1.32. Clearly, the daily percentage price change of silver is greater than 1 percent.

Table 1
Stylized facts of speculative markets

Series	Period	T	$r_{\min}$	$r_{\max}$	V	K	$\alpha_{5.0}$	H_r	$H_{\|r\|}$
DJI	1975–2000	6563	−25.6	9.7	0.70	71.1	3.53	0.47	0.76
DAX	1975–2000	6494	−13.7	7.3	0.81	12.3	3.10	0.51	0.80
DEM/USD	1974–1998	6264	−5.8	5.0	0.50	7.0	3.58	0.53	0.75
DEM/JPY	1974–1998	6264	−3.8	8.9	0.44	14.0	3.69	0.55	0.74
Gold	1975–2000	6509	−14.2	12.5	0.82	15.9	2.65	0.52	0.84
Silver	1975–2000	6557	−25.8	33.2	1.32	30.71	2.59	0.52	0.85

Daily data for the Dow Jones industrial average (DJI), the German share price index (DAX), mark–dollar (DEM/USD) and mark–yen (DEM/JPY) exchange rates, and gold and silver prices for 1 troyounce in USD.

Fat tails can be identified via the kurtosis K. Since the kurtosis of a normal distribution is 3, all time series of Table 1 exhibit excess kurtosis. However, the kurtosis is an unreliable estimator of fat-tailedness (Lux and Ausloos, 2002). Nowadays, fat tails are increasingly detected by the tail index α. A convenient method to compute the tail index is provided by the Hill tail index estimator (Hill, 1975). Note that the smaller the α, the fatter the tails. Using 5 percent of the largest observations delivers α-values between 2.59 (silver) and 3.69 (DEM/JPY). In addition, the tail index marks an upper bound of the existing moments of a distribution. Since α is below 4 for all samples, the fourth moment of the distribution of the returns does not exist.

Hurst exponents characterize the memory of a time series. Hurst exponents of around $H = 0.5$ indicate Brownian motion, whereas larger values hint at persistence and smaller values at anti-persistence. We have calculated Hurst exponents for raw returns and absolute returns using the DFA method (Peng et al., 1994; Ausloos, 2000; Lux and Ausloos, 2002). Raw returns seem to possess no memory because their Hurst exponents are close to 0.5. But volatility clustering is strongly supported. Hurst exponents for absolute returns hover at around 0.74 and 0.85.

2.2. On price limits

Price limits pre-specify the maximum range in which prices are allowed to move within a single day. The boundaries are typically determined by a percentage based on the previous day's closing price. Currently, price limits are used in many stock markets around the world, including France, Italy, Japan, Korea, Switzerland, Taiwan and the United States. The primary function of price limits is to stabilize the markets, that is to reduce volatility and mispricing. However, whether or not price limits succeed in this task is a somewhat unresolved issue. For surveys on price limits compare, for example, Kyle (1988), France et al. (1994) or Harris (1998).

Two rival opinions can be determined. One camp supports the overreaction hypothesis (Ma et al., 1989; Greenwald and Stein, 1991; Kodres and O'Brien, 1994), according to which traders tend to overreact to new information. Trading breaks give nervous traders time to cool off and to reassess their information. Against this background, price limits have the potential to moderate price fluctuations. The other camp (Fama, 1989; Lee et al., 1994; Kim and Rhee, 1997; Kim, 2001) believes in the information hypothesis. Prices are seen as unbiased estimates of fundamental values. Since price limits only slow down the adjustment of prices to a new equilibrium and have no effect on volatility, they are inefficient.

More specifically, the latter hypothesis refers to two aspects: delayed price discovery and volatility spillover. If the price discovery process is interrupted when an asset hits its price limit, then one would expect the price movement not to change direction in the next period. Traders tend to complete their pricing until the asset reveals its equilibrium value. Volatility spillover means that an asset that hits a limit should experience greater volatility in subsequent sessions compared to assets that do not hit the limit. Necessary price adjustments are simply postponed.

For Harris (1998), severe empirical problems make it impossible to reliably estimate the net effect of price limits. The difficulty stems from the myriad of reasons for which prices may change. For example, a decrease in volatility following the imposition of price limits may be due to completely unrelated factors: an increase in the number of fundamental traders, a period of greater political stability, or a higher transparency of firms' activity. Empirically, one may try to get around the problem of confounding explanations by examining large samples. However, such data sets are not available. In addition, the fundamental value of an asset cannot be determined accurately. Hence, it is neither possible to check how close prices are to fundamentals nor to decompose volatility into fundamental volatility and noise trader volatility.

To overcome these problems, we follow a different route of research. We try to develop a "realistic" model of traders' behavior which may be used as a laboratory to investigate the effectiveness of price limits. A simulation study has the advantage that one can control for all kinds of shocks, measure fundamental prices precisely and produce as many observations as required.

3. The laboratory model

3.1. Motivation

Traders within our model are boundedly rational in the sense of Simon (1955). Neither do they have access to all relevant information for price determination, nor do they know the mapping from this information to prices. In a complex world, agents thus lend themselves to a rule-governed behavior (Heiner, 1983). Fortunately, these rules are well documented so that we are able to approximate them for our purpose. Since our approach is based on empirical evidence, one may argue that it has an empirical micro-foundation. Lux and Marchesi (2000), among others, also use this route of underpinning. However, Hommes (2001) shows that the demand functions of the traders we employ in our model are congruent with myopic mean-variance maximizers. Our setting may thus also be embedded into a standard asset pricing model, the additional nonstandard features being agent heterogeneity and bounded rational expectations.

Let us briefly sketch the trading environment of the market participants. Empirical studies indicate that many markets are influenced, if not dominated, by the short-term speculative activities of its participants. For instance, the BIS (1999) reports that operations of intra-day traders account for 75 percent of total transactions in foreign exchange markets. Moreover, survey studies such as Taylor and Allen (1992) reveal that the traders use rather simple technical or fundamental trading rules to derive their orders. Only a small fraction of agents rely on one type of analysis. Most traders are familiar with both types of analysis and hold them to be complementary. Clearly, the weights given to the different rules vary according to market circumstances.

3.2. Setup

Our model works as follows. To determine their orders, traders apply both technical and fundamental trading strategies. The selection of a trading rule depends on its expected future performance. Traders who rely on technical trading rules are called chartists; agents who prefer fundamental analysis are called fundamentalists. Traders do not stick to one class of rule but repeat the selection procedure each trading period.

The term "technical analysis" is a general heading for a myriad of trading strategies. Its goal is to exploit regularities in the time series of prices by extracting (nonlinear) patterns from noisy data (Lo et al., 2000). Although there are probably as many methods of combining and interpreting the various techniques as there are chartists themselves, most rules subscribe to the notion of market momentum and rely on some sort of feedback mechanism (see Murphy (1999) for a popular manual on technical analysis). The demand of chartists in period t may be written as follows:

$$d_t^{\mathrm{C}} = \alpha^{\mathrm{C},1}(P_t - P_{t-1})/P_{t-1} + \alpha^{\mathrm{C},2}\delta_t. \tag{1}$$

The first term stands for trading positions triggered by a trend extrapolation of the current price P_t. The second term reflects additional random demand to account for the large variety of technical trading rules. δ is an IID normal random variable with mean zero and constant variance. The systematic and unsystematic components are calibrated with the positive reaction coefficients $\alpha^{\mathrm{C},1}$ and $\alpha^{\mathrm{C},2}$.

Fundamental analysis is built on the premise that the price of an asset moves towards its fundamental value F. The fundamentalists' demand may thus be expressed as

$$d_t^{\mathrm{F}} = \alpha^{\mathrm{F}}(F_t - P_t)/P_t, \tag{2}$$

where α^{F} is a positive reaction coefficient. Fundamentalists take a long (short) position if the price of an asset is below (above) its fundamental value.

Agents are assumed to perceive the fundamental price correctly. The evolution of F is due to the news arrival process and follows a random walk without drift. Its logarithm is given by

$$\mathrm{Log}\, F_t = \mathrm{Log}\, F_{t-1} + \eta_t, \tag{3}$$

where the news η is identically and independently distributed according to a normal distribution with mean zero and constant variance. A drift, often observable in stock markets, may easily be introduced in (3). Since our results are robust to such an extension we work with the driftless random walk in order to keep the model simple.

Traders repeat their decision for a trading rule every period, depending on expected future profit possibilities. These are identified as follows. If the distance between the spot price and the fundamental value rises, more and more agents conclude that the market is due for a correction. In such a situation, fundamental analysis is preferred to technical analysis. The weight of chartists may thus be defined as

$$m_t = \frac{1}{1 + \beta + \gamma_t\sqrt{|P_t - F_t|/F_t}}, \tag{4}$$

whereas the weight of fundamentalists is $(1 - m_t)$. The coefficient β represents a basic influence of the fundamentalists. Nevertheless, most traders choose their trading rule with respect to market circumstances. As indicated by (4), fundamentalism becomes more influential as the distance between P and F increases. The degree of fundamentalism critically depends on the popularity coefficient γ. The popularity of fundamentalism is not constant but changes over time as

$$\gamma_t = \gamma_{t-1} + (r^* - 100|P_t - P_{t-1}|/P_{t-1}) + \varepsilon_t. \tag{5}$$

The update takes place in two steps. The first step is due to risk considerations. If the most recent absolute relative price change is above (below) a long-term average absolute relative price change r^*, the popularity of fundamental analysis declines (rises). The intuition behind this adjustment is as follows. In turbulent periods, fundamental analysis is seen as less useful. As reported by Shiller (1990), traders tend to rely more on intuitive methods of price continuation or reversal in such periods. The second step incorporates communication among market participants. Traders exchange information about the usefulness of trading strategies and adopt the behavior of other agents. Communication is modeled as an IID normal random variable with mean zero and constant variance. The evolution of γ is restricted to $0 \leqslant \gamma_{\min} \leqslant \gamma_t \leqslant \gamma_{\max}$.

The excess demand of the market is given as the sum of all trading positions:

$$ed_t = m_t d_t^{\mathrm{C}} + (1 - m_t) d_t^{\mathrm{F}}, \tag{6}$$

and is mediated by the market makers. They supply excess demand from their inventory or accumulate inventory when there is an excess supply. Depending on the excess demand and their positive reaction coefficient α^{M}, the market makers quote the new price for the next period as

$$P_{t+1} = P_t + \alpha^{\mathrm{M}} ed_t P_t. \tag{7}$$

Clearly, (7) is an often used simplification of the real price discovery process in financial markets. It does not take into account possible large inventory imbalances of the market makers. Inventory management has recently been modeled by Farmer et al. (2002).

The price evolution equation is obtained by combining (1)–(7) and is given by

$$P_{t+1} = f(P_t, P_{t-1}, F_{t-1}, \beta_{t-1}, \delta_t, \eta_t, \varepsilon_t), \tag{8}$$

which is a four-dimensional nonlinear stochastic difference equation system (compare, for instance, Froyland (2001) for tools to analyze such systems). We proceed with a simulation analysis to demonstrate that the underlying structure gives rise to complex price fluctuations, as is observed empirically.

3.3. Calibration

Our aim is to calibrate the model to a broad range of speculative markets. Of course, every market has its own characteristics, but one should remember that the markets surveyed in Section 2.1 are basically influenced by the same type of trader and roughly share the same stylized facts. Specifically, we try to generate time series which mimic the dynamic properties of the daily data as summarized in Table 1 and Fig. 1. Table 2 displays our parameter setting for the simulations. With the help of these values, it should be easy to replicate the dynamics. Playing around with the parameter setting (within reasonable regions) reveals that the behavior of (8) appears to be surprisingly robust.

Table 2
Parameter setting for the simulations

$\alpha^{C,1} = 10$	$\alpha^{C,2} = 2$	$\alpha^{F} = 5$	$\alpha^{M} = 0.0125$	$\beta = 0.052$
$\gamma_{\min} = 0$	$\gamma_{\max} = 30$	$r^* = 0.75$	$\delta \sim \mathrm{N}(0, 1)$	$\varepsilon \sim \mathrm{N}(0, 1.75)$
$\eta \sim \mathrm{N}(0, 0.025)$	$S_1 = 99.75$	$S_2 = 100.25$	$F_1 = 100$	$\gamma_1 = 15$

3.4. Simulations

Figs. 2 and 3 give a first impression of the dynamics. Fig. 2 is designed to provide an intuitive understanding of what is going on in the market. The top panel contains the trajectories of the asset price and its fundamental value for the first 1000 periods. Two features are striking. Prices fluctuate erratically and may disconnect from fundamentals. Around period 300, a bubble emerges where prices deviate more than 20 percent from fundamentals. However, prices are very close to fundamentals between $t = 900$ and 1000. The second panel displays the corresponding return dynamics. Tranquil periods obviously alternate with turbulent periods.

The last two panels show the evolution of the popularity coefficient and the weight of chartists. In calm periods, the popularity of fundamentalism is high and the weight of chartists is low. But sharp price movements are also observable in these times. In period 60, the price changes roughly by 4 percent. Such outliers may occur if prices are close to fundamentals. In these times, the incentive to become a fundamentalist is weak and chartism dominates market action. If technical analysis delivers a clear trading signal, market makers have to absorb a high excess demand and trigger a strong price reaction.

If the popularity of fundamentalism declines, chartism becomes more influential. This in turn destabilizes the market and thus further weakens the use of fundamental analysis. Even if the distance between P and F is large (as around t=300), the majority of traders may use chartist methods.

Fig. 3 is based on a simulation run of 20,000 periods. The top panel visualizes relative deviations of prices from fundamentals which are mainly concentrated in a band of ±5 percent. For some periods, however, deviations increase up to 30 percent. To be more precise, let us define a measure of distortion as

$$D = \frac{100}{T} \sum_{t=1}^{T} |(P_t - F_t)/F_t|, \tag{9}$$

where T is the number of observations. D measures the extent to which prices fluctuate around the fundamental. For the first 20,000 observations D equals 3.84.

In the second panel, the return dynamics are plotted. Extreme price fluctuations are as large as 8.6 percent. We calculate volatility as

$$V = \frac{100}{T-1} \sum_{t=2}^{T} |(P_t - P_{t-1})/P_{t-1}|, \tag{10}$$

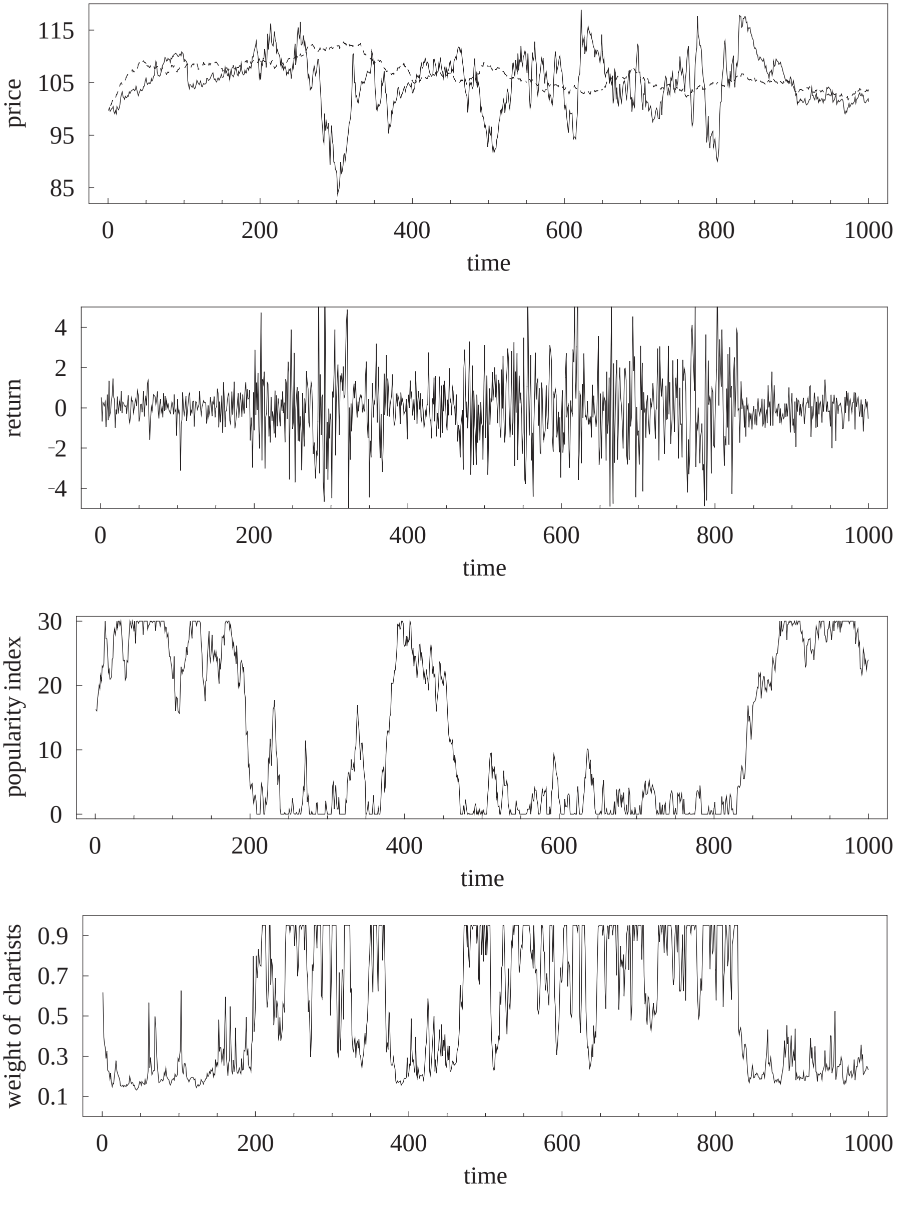

Fig. 2. The dynamics in the short run. The solid line in the top panel represents the asset price, the dashed line its fundamental value. The second panel shows the returns, the third panel the popularity of fundamentalism, and the last panel the weight of chartists. Parameters as in Table 2, 1000 observations.

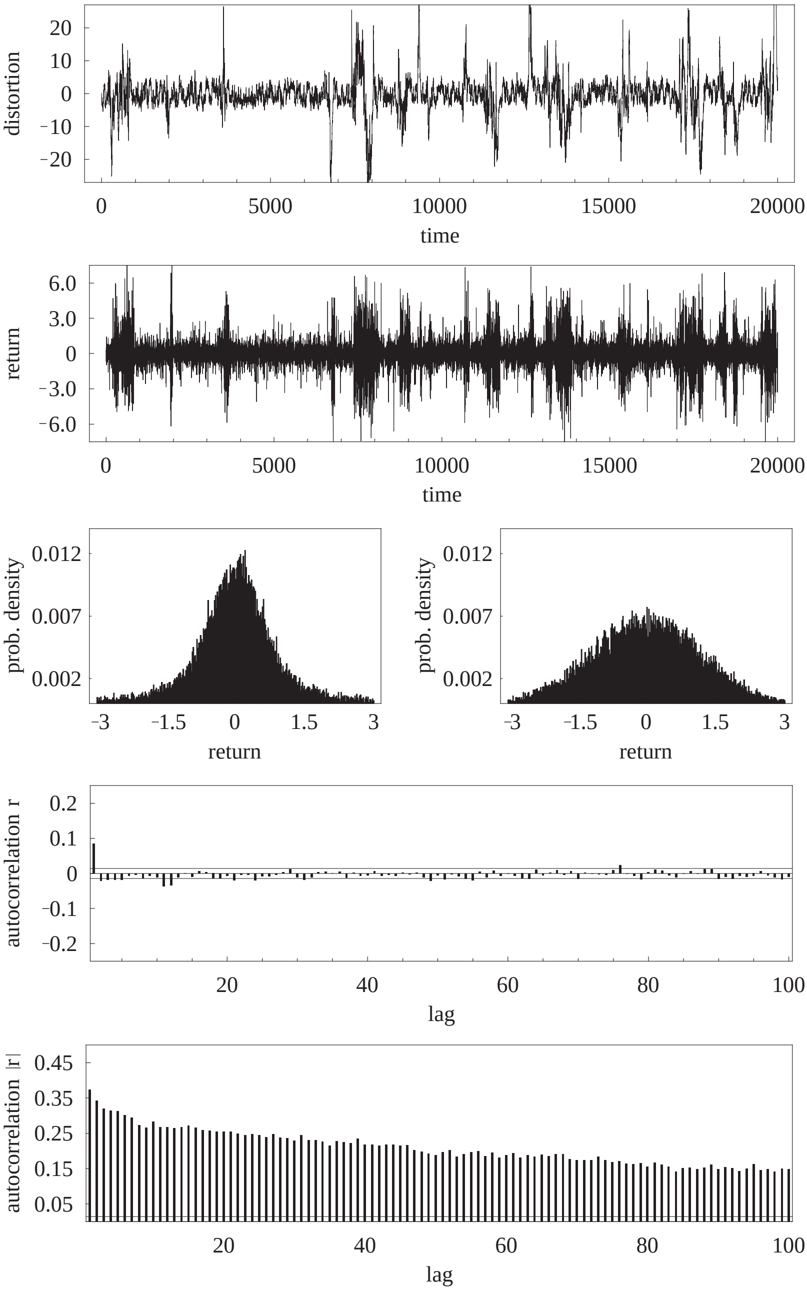

Fig. 3. The dynamics in the long run. The first panel shows the percentage deviations of the asset price from its fundamental value, the second panel the asset returns, the two central panels the probability density function for simulated returns (left) and normally distributed returns (right), and the last two panels the autocorrelation functions for raw returns and absolute returns with 95 percent confidence bands. Parameters as in Table 2, 20,000 observations.

Table 3
Some stylized facts of the model

	$r_{\min}$	$r_{\max}$	V	V^*	D	K	$\alpha_{5.0}$	H_r	$H_{\|r\|}$
Min	−7.4	7.2	0.81	0.2	4.0	7.4	3.21	0.37	0.86
Med	−8.0	8.4	0.82	0.2	4.2	7.7	3.41	0.38	0.87
Max	−9.3	9.0	0.83	0.2	4.5	8.8	3.47	0.42	0.88

Parameters as in Table 2, minimum, median and maximum values for 10 simulation runs, each containing 20,000 observations.

which delivers a value of $V = 0.80$. As suggested by Guillaume et al. (1997), we prefer absolute values to the more usual squared values. Due to the nonexistence of the fourth moment in the distribution of the returns, the former quantity has a greater capacity to reflect the structure in the data. The random walk process of the fundamental F produces a volatility of $V^* = 0.2$. Since V is 4 times larger than V^*, the activity of the traders creates excess volatility.

The two central panels show the probability density function for simulated returns (left) and for normally distributed returns (right). The fat tail property is obvious and is supported by estimates of the kurtosis and the tail index. The last two panels show the autocorrelation function for raw returns and absolute returns. The model generates strong volatility clustering.

Table 3 presents a summary of the stylized facts for 10 randomly selected simulation runs. It reports the minimum, median and maximum values of the computed statistics. Comparing Tables 1 and 3 allows us to conclude that the model delivers a good fit of the empirical data. Hence, we proceed with our analysis and perform some laboratory experiments to test the effectiveness of price limits.

4. The effectiveness of price limits

The behavior of traders remains as described in the previous section. However, the price adjustment of the market makers is restricted to

$$P_t(1 - i/100) < P_{t+1} < P_t(1 + i/100), \tag{11}$$

where i stands for the maximum allowed percentage price change per period. If the limit is reached, trading is stopped for that period. In the next period, trading is resumed as usual.

How does such a trading break affect volatility and distortion? Fig. 4 contains the outcome for the following simulation design. The dotted lines in the left-hand panel demonstrate how volatility reacts to less stringent price limits. The price limits are increased in 100 steps from 0 to 5 percent. For each price limit, the volatility is calculated from 20,000 data points. The time series are generated using the parameter setting of Table 2. This is repeated for 10 different seeds of random variables. The right-hand panel displays the same for the distortion. The solid lines mark the averages.

For $i = 0$, volatility is, of course, eliminated. However, distortion is extremely large. With increasing price limits, volatility continuously climbs until it reaches its no-price-limit value. The picture for distortion is different. From $i = 0$ to 0.4, the distance between prices and fundamentals shrinks, but then grows again.

In our model, trading breaks work as follows. Since price limits cut down sharp price movements, technical trading signals are less pronounced. A reduction of positive feedback trading reduces the excess demand market makers have to equilibrate. In addition, lower price fluctuations make fundamental analysis more popular (i.e. γ rises) so that markets continue to calm down. Two aspects counter these forces. First, the closer the prices are to fundamentals, the more the traders prefer technical analysis. Although this effect increases volatility, it is not strong enough to overcompensate the others. Second, if price limits are too restrictive, necessary price adjustments after the occurrence of fundamental shocks are slowed down. Hence, the distortion grows.

What are the policy implications? The regulator faces a conflict of interests. For price limits below $i \approx 0.4$, volatility declines and distortion rises. To determine the optimal level of i, the welfare function of the regulator has to be known. Nevertheless, it is clear that weak price limits are better than having no price limits. They offer a method of stabilizing speculative markets: both volatility and distortion are reduced.

Fig. 4 illustrates one problem that empirical studies have to account for. Suppose we want to evaluate the effectiveness of trading breaks and thus compare a market with a price limit of 2 percent with a market without such restrictions. Although we have access to 20,000 observations, volatility scatters for $i = 2$ in the range of 0.6–0.7. Since the volatility for a no-price-limit scenario is approximately indicated by the right end of a dotted line, trading halts moderate fluctuations in all cases. However, a comparison of $V = 0.7$ with the bottom no-price-limit V value would lead us to the wrong conclusion that price limits fail to stabilize the markets. The dispersion of

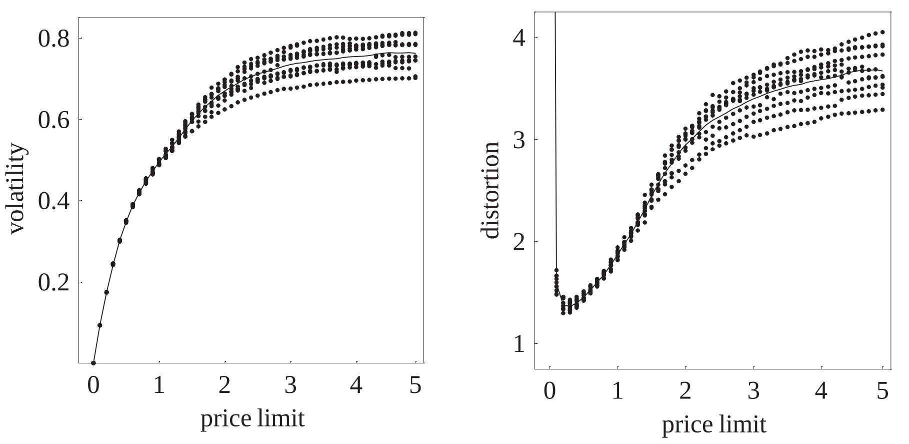

Fig. 4. The effectiveness of price limits. Price limits range between 0 and 5 percent, increasing in 100 steps. Volatility and distortion are calculated from 20,000 observations. Parameter setting as in Table 2, 5 different seeds of random variables. The solid lines indicate the averages.

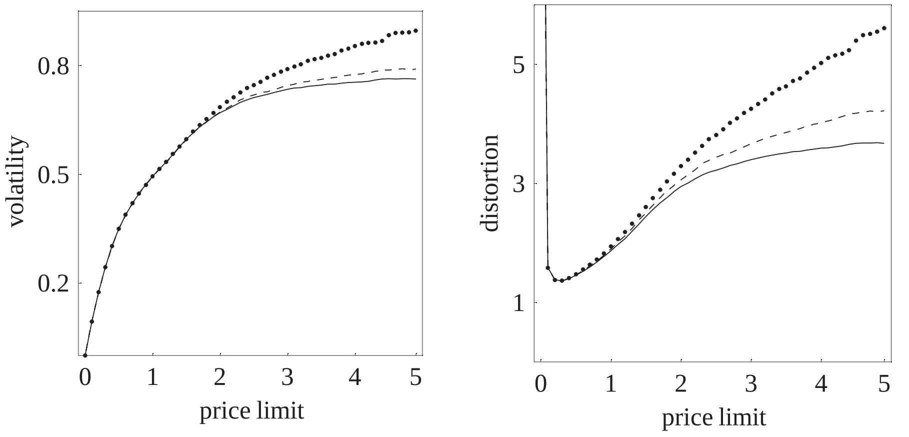

Fig. 5. Price limits and trend extrapolation. Volatility and distortion are plotted for rising price limits (average values for different seeds of random variables, calculated in the same way as for the solid lines in Fig. 4). Parameters as in Table 2, but for the solid line $\alpha^{C,1} = 10$, for the dashed line $\alpha^{C,1} = 30$, and for the dotted line $\alpha^{C,1} = 50$.

V is caused by volatility clustering. The level of volatility crucially depends on how often the system jumps from tranquil regimes to turbulent regimes. Interpreting our data as daily data means that we have a data record of 80 years (assuming 250 trading days per year). Such large data samples are typically not available.

In some periods, chartists collectively pay more attention to positive feedback rules. Fig. 5 compares the effectiveness of price limits for different degrees of bandwagon behavior. Remember that the larger the $\alpha^{C,1}$, the stronger the chartists extrapolate recent price movements into the future. In the left (right) panel of Fig. 5, the reaction of the volatility (distortion) is plotted against rising price limits. The solid lines represent $\alpha^{C,1} = 10$, the dashed lines are $\alpha^{C,1} = 30$, and the dotted lines show $\alpha^{C,1} = 50$ (average values for different seeds of random variables, as in Fig. 4). Obviously, the more strongly the traders rely on trend extrapolation, the greater the success of price limits.

Price limits have met with a certain amount of approval by politicians since the 1987 stock market crash, but the academic world is still largely skeptical about their effectiveness. For Fama (1989), this crash was nothing more than a breathtaking quick adjustment of prices towards fundamentals. Since fast adjustments increase welfare, the performance of the market during the crash is to be applauded. Rules that prevent the market from collapsing are irrelevant.

Our evidence suggests a different conclusion. Of course, Fama is right in saying that a quick price discovery process is desirable. However, he seems to overlook that the extent of a bubble may be reduced by price limits. Remember that in our model a bubble is likely to emerge when chartists gain prominence. The more agents rely on positive feedback strategies, that is, the more the agents trade in the same direction, the more the market makers are forced to adjust prices in that direction. During volatile periods, trend-extrapolating behavior gains more and more influence. The dynamics gain a self-fulfilling character. Our simulations show that price limits allow the amplitude of the fluctuations to be attenuated.

5. Conclusions

Although each asset market has its own characteristics, many of them show strikingly similar stylized facts. These universal features seem to originate from the trading activity of their market participants. Motivated by empirical observations, the chartist–fundamentalist approach explicitly models the behavior of interacting heterogeneous agents. For instance, contributions such as those of Kirman (1991), Brock and Hommes (1997, 1998) and Lux and Marchesi (2000) give a realistic description of traders' behavior and are able to replicate the main properties of asset price dynamics. Since some of the traders rely on positive feedback rules, volatility appears to be excessive and prices are occasionally driven away from fundamentals.

To evaluate the effectiveness of price limits, we have tried to develop a laboratory to study how trading breaks may affect price dynamics. One advantage of such analysis is that one can control for all kinds of shocks and generate as many observations as needed. Our simulations suggest that price limits are welfare-improving: prices become less volatile and less distorted. Price limits are particularly promising during periods in which traders strongly engage in bandwagon behavior. Trading breaks work via two channels. Technical trading signals triggered by positive feedback rules are weakened and fundamental analysis is encouraged.

Of course, our results are preliminary. The mechanism through which trading breaks affect price dynamics depends on the structure of the model. Other factors may reinforce or diminish their effectiveness. More work is needed. Hopefully, our study will enrich the debate on price limits. In addition, we firmly believe that laboratories based on chartist–fundamentalist models have the potential to improve the understanding of the working of regulatory means.

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